

Scanning multichannel microwave radiometer snow water equivalent assimilation

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[1] Accurate prediction of snowpack status is important for a range of environmental applications, yet model estimates are typically poor and in situ measurement coverage is inadequate. Moreover, remote sensing estimates are spatially and temporally limited due to complicating effects, including distance to open water, presence of wet snow, and presence of thick snow. However, through assimilation of remote sensing estimates into a land surface model, it is possible to capitalize on the strengths of both approaches. In order to achieve this, reliable estimates of the uncertainty in both remotely sensed and model simulated snow water equivalent (SWE) estimates are critical. For practical application, the remotely sensed SWE retrieval error is prescribed with a spatially constant but monthly varying value, with data omitted for (1) locations closer than 200 km to significant open water, (2) times and locations with model-predicted presence of liquid water in the snowpack, and (3) model SWE estimates greater than 100 mm. The model error is estimated using standard error propagation with a calibrated spatially and temporally constant model error contribution. A series of tests have been performed to assess the assimilation algorithm performance. Multiyear model simulations with and without remotely sensed SWE assimilation are presented and evaluated with in situ SWE observations. The SWE estimates from assimilation were found to be superior to both the model simulation and remotely sensed estimates alone, except when model SWE estimates rapidly and erroneously crossed the 100-mm SWE cutoff early in the snow season.

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1. Introduction

[2] Previous modeling and observational studies have demonstrated that snow is an important climatic driver through the surface albedo's role in energy and water budgets [e.g., Yeh *et al.*, 1983; Namias, 1985; Barnett *et al.*, 1989; Yang *et al.*, 1999, 2001; Cohen and Entekhabi, 1999]. Models have an advantage over in situ observations in such climatic studies as they provide global estimates of the spatial and temporal variation in snowpack conditions, while in situ observations are limited in both space and time. Moreover, models are able to quantitatively describe the relationship between snowpack status and water and energy balance, enabling the climate system feedback to be fully explored. However, models are also limited by a number of factors. For example, successful snow evolution

prediction is challenging due to immature knowledge of snow evolution physics, simplifications in model parameterizations, high spatial and temporal variability of snow cover, and errors in the model forcing data [e.g., Lynch-Stieglitz, 1994; Rodell *et al.*, 2004].

[3] Space-borne passive microwave sensors provide an alternate capability to monitor global-scale snow evolution, yielding 1- to 3-day repeat snow water equivalent (SWE) measurements at approximately 25- to 50-km resolution. Such sensors include the scanning multichannel microwave radiometer (SMR), the special sensor microwave imager (SSM/I), and the advanced microwave scanning radiometer for the Earth (AMSR-E) observing system. Many investigators have carefully evaluated the accuracy of remotely sensed SWE, suggesting good prairie region performance but poor boreal forest and high latitude tundra region performance [e.g., Robinson *et al.*, 1993; Tait and Armstrong, 1996]. To overcome these limitations, Foster *et al.* [2005] derived an alternate algorithm that made systematic error adjustments based on environmental factors including forest cover and snow morphology (i.e., crystal size as a function of location and time of year). While this yielded an improvement in SWE estimates, the SWE estimates were affected by signal saturation above a SWE of approximately 100 mm, mixed pixel contamination for regions within 200 km of large, open water bodies, and liquid water in the snowpack for monthly air temperatures above -2°C [Dong *et al.*, 2005]. Although this limits the use of remotely sensed SWE estimates to inland locations for times of moderate snowpack amount, it is at these times and locations that the snowpack is

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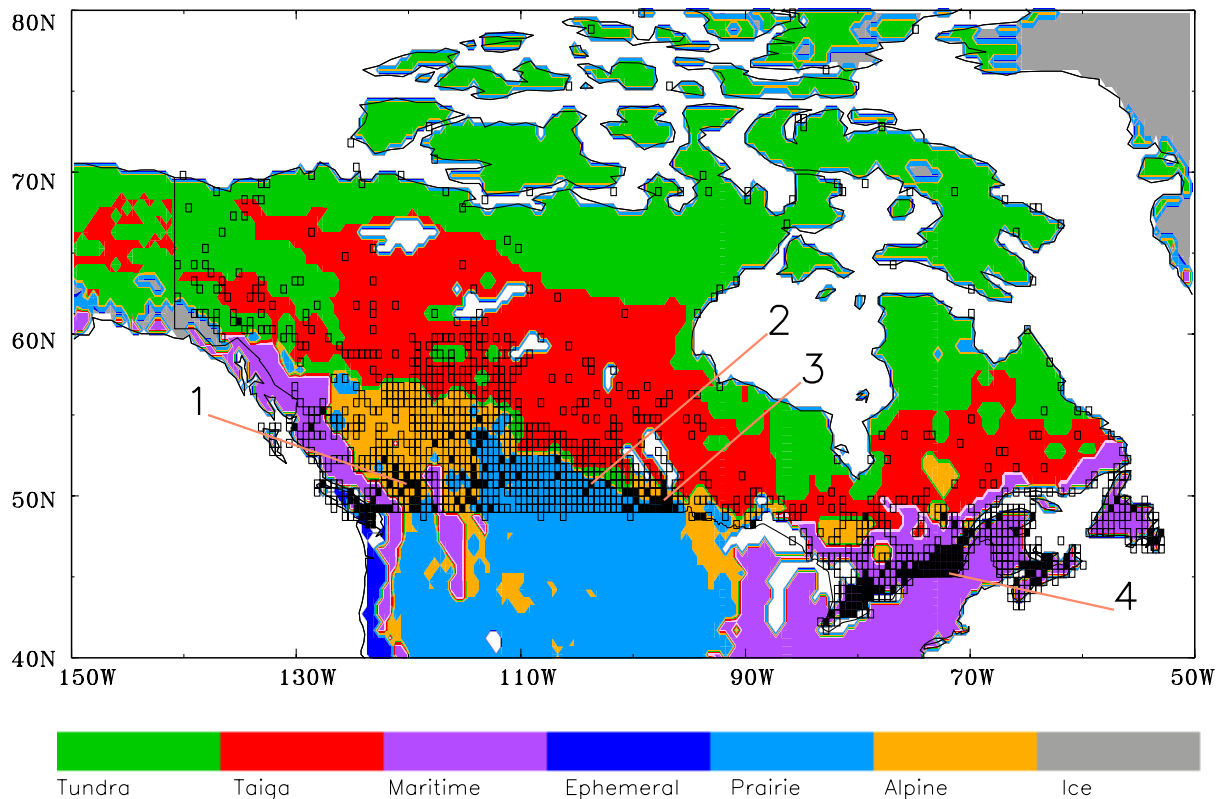


Figure 1. Spatial distribution of all half-degree by half-degree grid cells including one to four in situ SWE stations (open squares) and five or more in situ stations (solid squares), with the background colors showing snow classification according to *Sturm et al.* [1995]. The numbers 1 to 4 indicate selected pixels used in subsequent analysis.

typically the most dynamic and model estimates are the poorest [e.g., *Slater et al.*, 2001].

[4] As both model predictions and remotely sensed estimates are characterized by different uncertainties at different times and locations, the most accurate snowpack status estimate results from the assimilation of remotely sensed estimates into a land surface model, with correct observation and model error specifications. The SWE estimation improvement using data assimilation can be verified using nonassimilated in situ data. In order to attain this optimal snowpack state estimate, it is essential that the assimilation scheme account for the relative uncertainty of both model predictions and observations. For example, direct replacement of the modeled snow states with observations by assuming that the observations are without any error can often yield degraded model predictions in certain situations [e.g., *Liston et al.*, 1999; *Rodell and Houser*, 2004]. Moreover, direct replacement of SWE has only a minimal impact on errors of correlated snow state estimates, such as snowpack depth and temperature.

[5] Several recent studies have applied the Kalman filter to the assimilation of snow cover and snow water equivalent in land surface and hydrological models, and their synthetic experiments showed improved streamflow and SWE simulation accuracy [Sun *et al.*, 2004; *Andreadis and Lettenmaier*, 2006; *Clark et al.*, 2006; *Slater and Clark*, 2006]. An advanced assimilation system has recently been developed to perform SWE assimilation with a one-dimensional extended Kalman filter (EKF) by Sun *et al.* [2004]. Their results from a series of identical-twin experiments have clearly demonstrated that poor initial condition

effects can be removed, and runoff and atmospheric flux predictions improved in the absence of significant model and/or observation error [Sun *et al.*, 2004]. As significant model and remotely sensed SWE errors often exist in reality, assimilation of satellite-derived SWE and verification with actual in situ observations are challenging.

6. Conclusions

[32] Spatially complete and temporally continuous uncertainty maps for both remotely sensed and land surface model SWE estimates have been generated and evaluated. The remotely sensed SWE retrieval uncertainty is prescribed by a spatially constant monthly varying value, with data omitted under three considerations: (1) locations closer than 200 km to significant open water, (2) presence of liquid water in the snowpack, and (3) model SWE estimates greater than 100 mm. Model SWE uncertainty has been calibrated by tuning a spatially and temporally constant model error term used in the error propagation equations to the observed model error.

[33] A series of numerical experiments have demonstrated that assimilation of remotely sensed SWE estimates results in improved SWE estimates when compared to in situ measurements. However, when poor-quality observations are assimilated or the model simulation transitions are quickly beyond the 100-mm SWE cutoff, the assimilation algorithm is no longer able to improve the snowpack simulation. Comparison between the open-loop and assimilation simulations shows that runoff and upward short and long wave radiation are also modified through assimilation of remotely sensed SWE.